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MULTISPECTRAL IMAGE PROCESSING FOR PLANTS

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Abstract

The development of a machine vision system to monitor plant growth and health is one of three essential steps towards establishing an intelligent system capable of accurately assessing the state of a controlled, ecological life support system for long-term space travel. Besides a network of sensors, simulators are needed to predict plant features, and artificial intelligence algorithms are needed to determine the state of a plant based life support system. Multispectral machine vision and image processing can be used to sense plant features, including health and nutritional status.

Summary

Low-pass, spectral filters added to a CCD camera and digital image processing were used to sense the multispectral reflectance from potato leaves and measurements were compared to laboratory standard reflectors and to a multispectral sensor. The techniques developed for multispectral imaging satisfactorily measure leaf reflectance. The results for black and white images were well correlated to the multispectral sensor for bright surfaces, but not so well for dark ones. Full, 24-bit color images with spectral filters could be used to further explore the application of machine vision to sense plant health and nutrition status.

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INTRODUCTION

1.1 Plants

Plants grown for food are necessary components of life support systems for long-term, manned space voyages. Current research on controlled, ecological life support systems (CELSS) has shown that plants grown in liquid cultures may rapidly develop health or nutrient problems which degrade the performance of a CELSS. If this situation were to occur on a long term voyage, it would pose a serious threat to the crew's food supply and life support system.

1.2 Sensors

Sensors which monitor plant features could be used to provide feedback to environmental controls and to the nutrient delivery system. Alarms could be activated when plant features exceed predetermined limits. Active monitoring of the plants provides positive feedback for control systems. Sensors which monitor environmental conditions (carbon dioxide, oxygen, ethylene, etc.) or nutrient concentrations are indirectly monitoring the plants and the data may be difficult to interpret. For instance, does an increase in carbon dioxide level mean the plants are fixing less carbon from the atmosphere, or that plant respiration has increased? or that respiration has increased in a bioreactor digesting inedible plant materials?

Many features of plants are sensible. Plants grow in size and change shape with age, leaves move in response to light, stems and leaves shrink and swell with water content. Root tips of healthy plants grow approximately 3 microns per minute. Plant nutrient deficiencies (Al-Abbas, et al., 1974) and molds (Ruiz and Chen, 1982) have been sensed by measuring the spectral reflection of light from leaves. Stutte, Bors and Stutte, 1989, measured decreases in reflectance between 710 to 1100 nanometers 7 days before symptoms of nitrogen deficiency were visible in laboratory grown plants. Miles, 1989, used machine vision to quantify iron, nitrogen, and potassium deficiencies and water stress in wheat seedlings.

1.3 Information

The data from sensors, including machine vision, must be processed to extract desired features and to resolve conflicts between sensors. This processing provides knowledge of conditions such as severity of moisture stress and stage of growth. Miles, 1989, used a Sobel operator to detect edges of leaves, then compared the absolute and relative amounts of green in the image to determine nutrient stresses. Additional algorithms could perform operations

such as edge following to detect features such as marginal necrosis which is a symptom of potassium deficiency in wheat.

1.4 Intelligence

The ultimate use of a sensor is to provide the basis for determining the state of a CELSS: **Good**, **Bad**, or **Ugly**. When the life support system is on course, that is, conditions are **good**, nothing needs to be done. When the life support system is off course, but knows what has happened and is correcting back to course, conditions are **bad**. When the life support system has failed, or failing, that is, it is lost, then conditions are **ugly**. Classifying the CELSS into one of these states requires not only the basic data and information, but the intelligence to know where the life support system should be. This requires algorithms to distinguish features well enough to identify the source of the problem. For example, lower levels of green in a leaf image may be due to nitrogen deficiency; but is that caused by a lack of an essential nutrient in the solution feeding the plant roots, or is it due to a deficiency of oxygen to the roots (such as occurs when field crops "drown" with excess water).

Intelligence also requires a system of differential equations relating plant growth and development to environmental conditions, ie, a model. Such a model must be able to predict the magnitude of sensible features, thereby providing a targeted course for comparison.

One form of intelligence is an expert system such as the muskmelon disorder diagnostic system written in CLIPS, a C-based development shell (Latin, et al., 1989). In such a system, rules are built in the form: IF...THEN...ELSE. When the if conditions are met, then the action is taken. The action could be to fulfil the conditions of another if statement. Ultimately the rules seemingly provide the intellect process of an expert when confronted with the same set of conditions.

1.5 Solution

Determining whether the state of a CELSS is **good**, **bad**, or **ugly** requires a three pronged effort. The first is to develop an integrated network of sensors monitoring the plants and environmental conditions. This will include but not be limited to machine vision systems. The second effort must be the development of models which predict the occurrence and magnitude of features such as leaf area, flowering, and so forth. Equations in the models may well predict other, internal (not sensible without destructive sampling) parameters, but the essential output is detectible features. The third effort is to develop an intelligent

program capable of interpreting information from the sensor network, comparing it to model predictions and assessing the state of the system. The program could be a combination of numerical simulation, expert systems, neural networks and other artificial intelligence algorithms.

This work will focus on the development of a sensor to monitor the growth, health, and nutritional status of plants.

1.6 Objectives

The objectives of this project are:

1. Develop techniques to capture and process spectral images using machine vision, and
2. Determine the relationship between the machine vision sensor and a multispectral sensor.

PROCEDURES

2.1 Plants

Norwood potatoes were grown in Chamber 5, Hanger L, at elevated levels of carbon dioxide (10000 ppm). Normal chamber lighting was provided by a combination of Vita-Lite and Daylight fluorescent bulbs. The spectrum of the incident light (Figure 1) was measured with a LICOR spectral radiometer. For half the images, an Halogen lamp was used to illuminate the potato leaf.

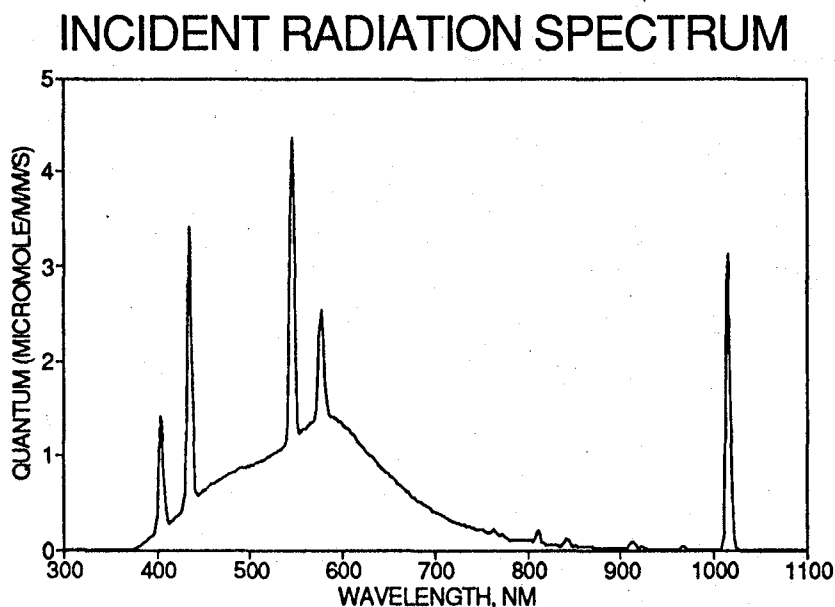


Figure 1. Incident Radiation Spectrum in Chamber Produced by Vita-Lite and Daylight Fluorescent Lights.

2.2 Machine Vision

Images of a Norwood potato leaf (Figure 2) were sensed by a Panasonic CCD camera. The VHS output of the camera was digitized by a Videopix frame grabber installed in a Sun Microsystems Sparc 2 workstation. Software supplied with the Videopix card, **vfctool**, was used to capture and store the image as an 8 bit black and

white, **tiff** file. Melles Griot 40 nanometer wide band-pass filters (450, 550 and 650 nanometers) were secured in a modified step ring and attached to the front of the camera lens to provide the filtered images. An 850 nanometer filter was tried, but the resultant image was too dark to distinguish any of the plant features, so it was not processed.

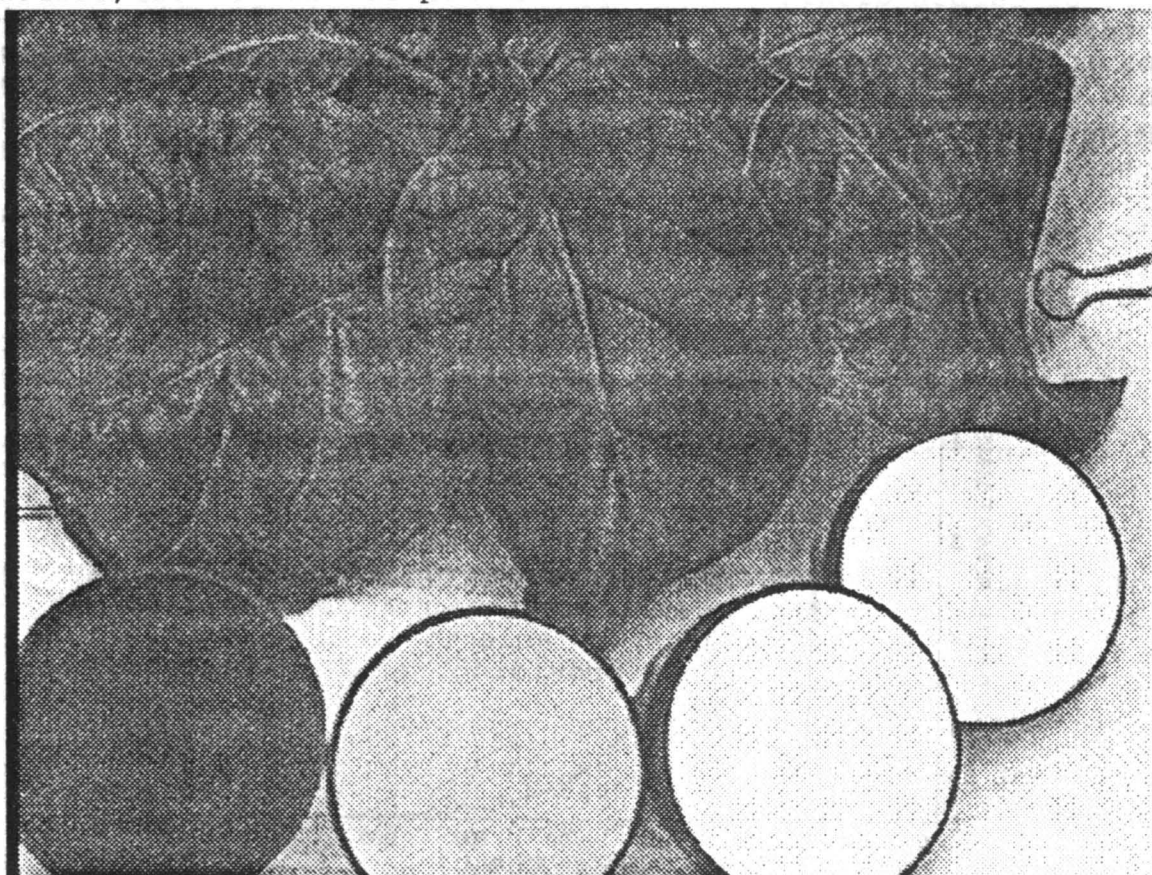


Figure 2. Norland Potato Leaf With Standard Reflectors.

Laboratory standard reflectors were placed around the leaf to provide calibration data. In Figure 2, the standards are from left to right, 2%, 25%, 75% and 100%.

After the images were captured and stored on disk, **sunvision** was used to position a window 50 x 50 pixels over each standard reflector and over the right, middle and left sections of the center potato leaf. The menu-driven **ip** software contained in **sunvision** was used to compute the maximum, minimum, median, mean and standard deviation of the gray level values in each window. Because only the 8-bit black and white image was saved (a 24-bit color image from the Videopix card requires over 900 K bytes of storage), the maximum gray level value is 255. Statistics for the left, middle and right windows of the leaf were summed and divided

by three to compute an average.

2.3 Agave Multispectral Sensor

Just before and after the machine vision data were captured, personnel from Agave Analytics used a multispectral sensor (a Spectron Model CE 390 wideband camera) to record the entire spectra of light reflected from the potato leaf and each of the standards. The results reported are the weighted average of the reflectance spectrum of the leaf over the wavelength range of the corresponding filter. The product of the reflectance of the leaf and that of the filter was summed over the wavelength ranges 401 to 501, 502 to 604, and 605 to 700 nanometers for the 450, 550, and 650 nm filters, respectively. The reflectance of the filter is actually a transmittance spectra obtained by ratioing the spectrum for the 100% standard with the filter, to the 100% standard without the filter. The *no filter* data were calculated by summing the reflectance for the leaf over the interval 401 to 700 nm with a weight factor of one, then dividing by the number of channels (102) to average.

RESULTS AND DISCUSSION

3.1 Machine Vision

Figures 3 and 4 illustrate the relationship between the average gray level values obtained by the machine vision system and the laboratory standard reflectors for the normal chamber lighting and the added Halogen light treatment. The *no filter* gray level values are universally greater than any of the filtered curves. Between 25% and 100% reflectance, the relationship appears to be linear, but the 2% reflectance values deviate considerably from the straight line model. The addition of the Halogen lamp did not increase the gray level values; in fact they decreased, for some unknown reason. The barcharts in Figures 5, 6, 7 and 8 compare the filter performance for each reflectance standard. In general, the longer wavelength filter apparently reduces the gray scale values, with the exception of the 550 filter where the values are slightly higher than the 450 and 650 ones. The filters do have a significant affect on the gray levels recorded by the machine vision system. The reflectance standard also has a significant affect on the gray scale values. The machine vision system appears to be very sensitive to the low reflectance, that is the dark standards. Most of the change in gray level values occur between 2% and 25% reflectance.

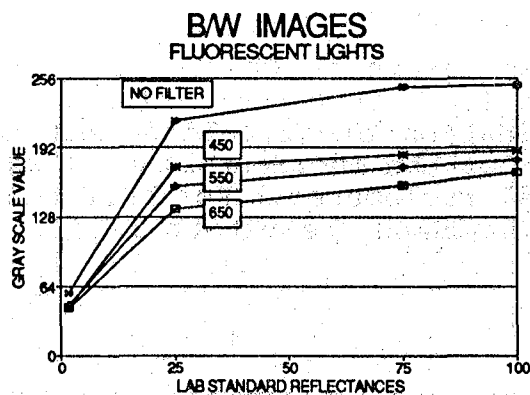


Figure 3. Machine Vision Measurement of Standard Reflectors with Fluorescent Lights.

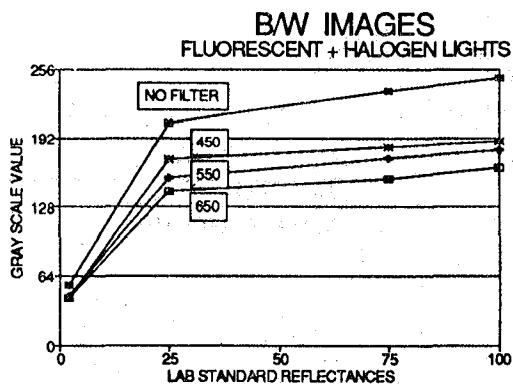


Figure 4. Machine Vision Measurement of Standard Reflectors with Fluorescent and Halogen Lights.

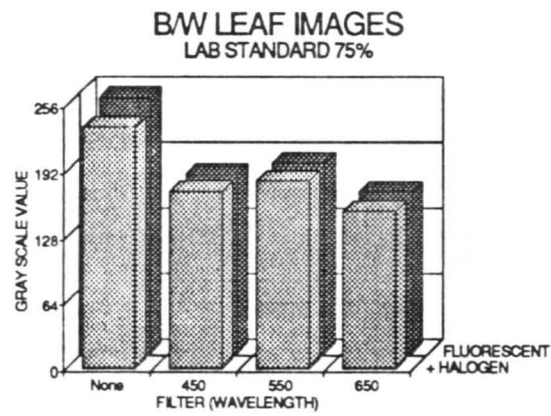


Figure 5. Machine Vision Measurement of 75% Reflector.

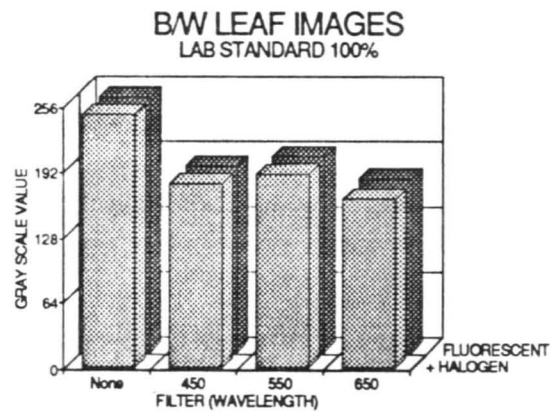


Figure 6. Machine Vision Measurements of 100% Reflector.

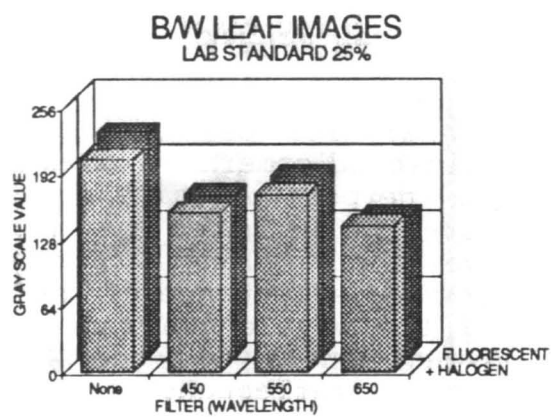


Figure 7. Machine Vision Measurement of 25% Reflector.

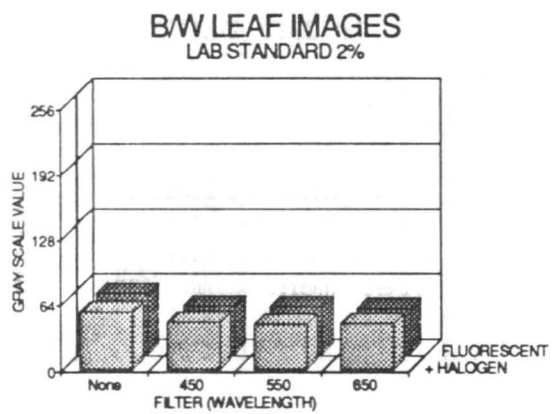


Figure 8. Machine Vision Measurement of 2% Reflector.

Figures 9 and 10 present the gray scale reflectors for the potato leaf. In general, the values are much less than the standards, and indicate the leaf reflects approximately 25% as much as the *white* reflectance. The middle window of the leaf has slightly higher gray scale values than the left or right windows, possibly because it contains the midrib. When Halogen light is added, the difference between the middle and sides is even greater. This may mean that differences in the reflectance of light in the near infrared region may be a means of identifying the midrib feature in machine vision images of potato leaves. For the purposes of this study, the differences were considered small, and an overall leaf average used in the remaining comparisons. Figure 11 compares all the reflectance standards to the leaf for the *no filter* treatment. From this figure it is apparent that leaf reflectance is between the 2% and 25% standards.

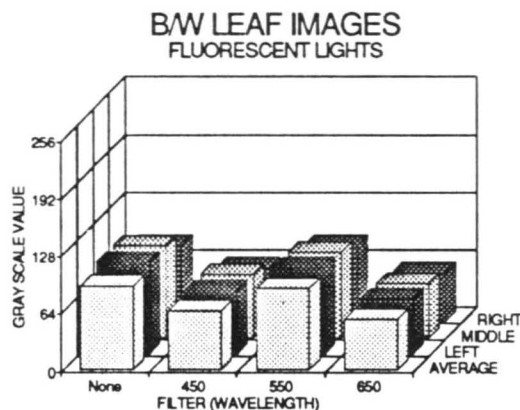


Figure 9. Machine Vision Measurement of Potato Leaf with Fluorescent Lights.

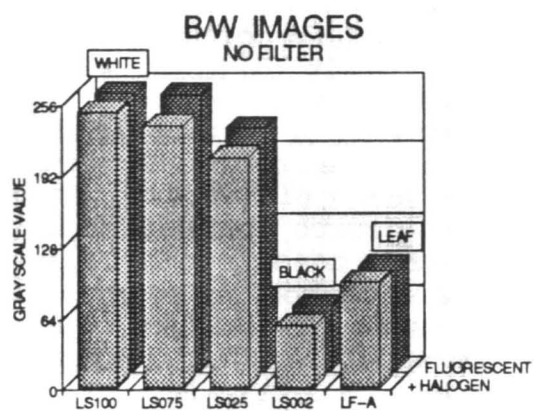


Figure 10. Summary of Machine Vision Measurements without a Filter.

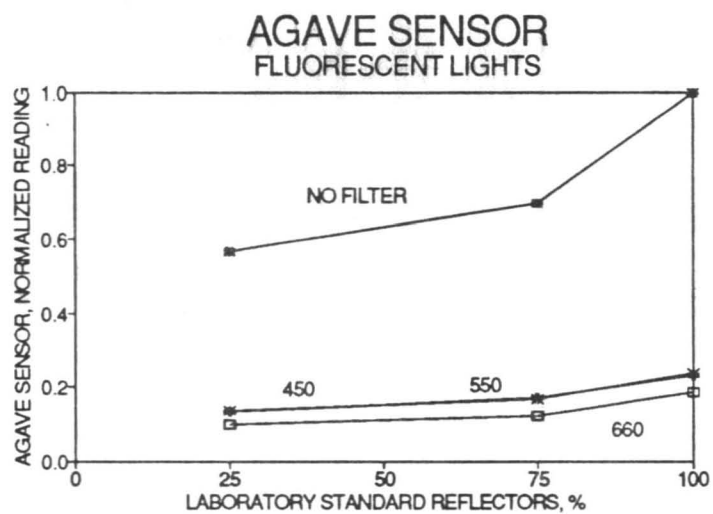


Figure 11. AGAVE Multispectral Sensor Measurement of Standard Reflectors with Fluorescent Lights.

3.2 Agave Multispectral Sensor

Figures 12 and 13 contain the results for the Agave multispectral sensor measurements of the standard reflectance surfaces. The no filter readings are significantly higher than the filtered treatment readings. The 450 and 550 nm readings are practically identical to each other. The Halogen light did not add much to the readings. From 25% to 100% reflectance, the multispectral readings increase, but in a nonlinear fashion.

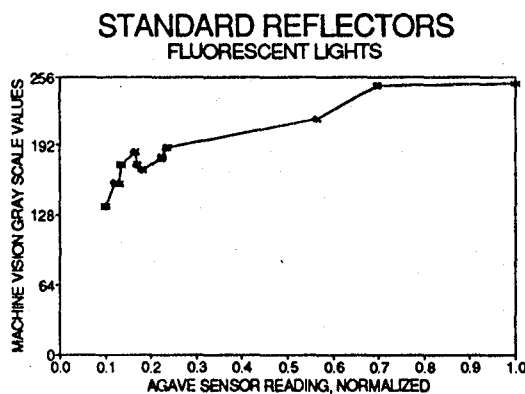


Figure 12. Machine Vision versus Multispectral Sensor Measurement of Standard Reflectors with Fluorescent Lights.

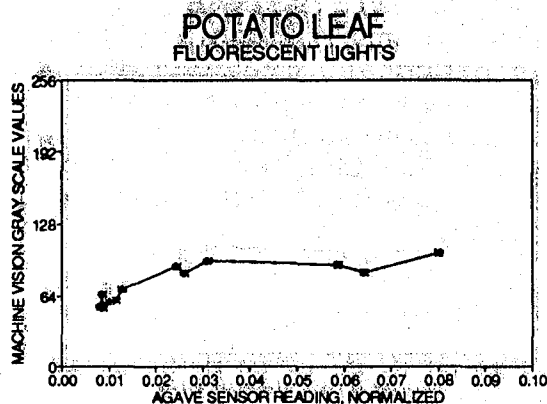


Figure 13. Machine Vision versus Multispectral Sensor Measurement of Norland Potato Leaf with Fluorescent Light.

3.3 Machine Vision versus Multispectral Sensor

Figures 14 and 15 compare the machine vision gray scale values to the readings obtained from the multispectral sensor for the standard reflectors. For multispectral readings above .3, there appears to be a strong, positive correlation. However, below that point, there are some disturbing variations. Equations 1 and 2 have R^2 values greater than 0.92, but most of the variance is at the low readings of the multispectral sensor.

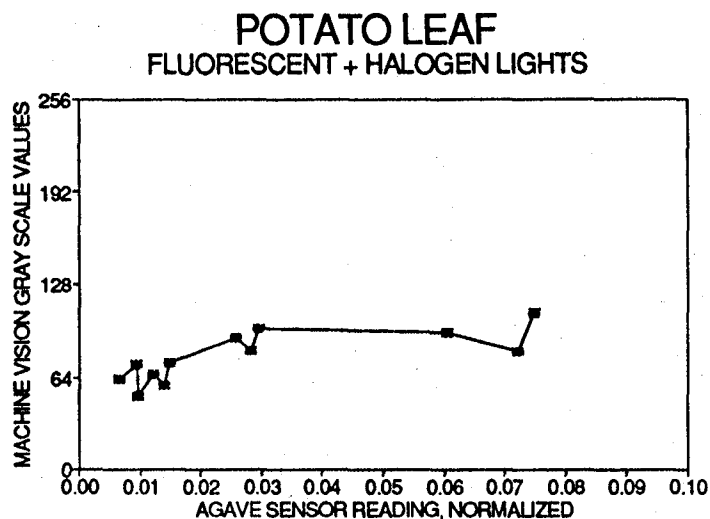


Figure 14. Machine Vision versus Multispectral Sensor Measurement of Norland Potato Leaf with Fluorescent and Halogen Lights.

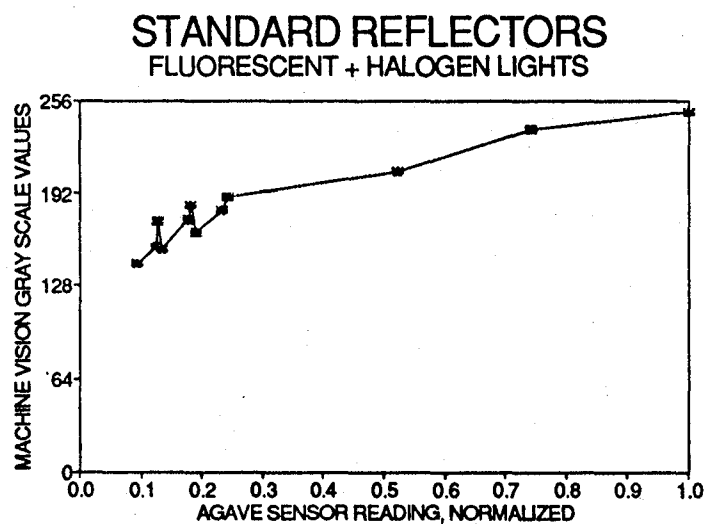


Figure 15. Machine Vision versus Multispectral Sensor Measurement of Standard Reflectors with Fluorescent and Halogen Lights.

$$Y = -135.51X^2 + 253.16X + 130.94, R^2 = 0.92$$

$$Y = -87.13X^2 + 196.21X + 137.15, R^2 = 0.93$$

That's the range of leaf readings, as seen in Figures 16 and 17. The scales of these two figures have been changed to illuminate any relationship. It does not appear that the relationship between the machine vision sensor and the multispectral sensor is strongly correlated for leaf reflectors. Equations 3 and 4 have R^2 values of .8 or less.

$$Y = -0.0001753X^2 + 0.001942X + 46.51, R^2 = 0.70$$

$$Y = -0.0001558X^2 + 0.001827X + 45.5, R^2 = 0.80$$

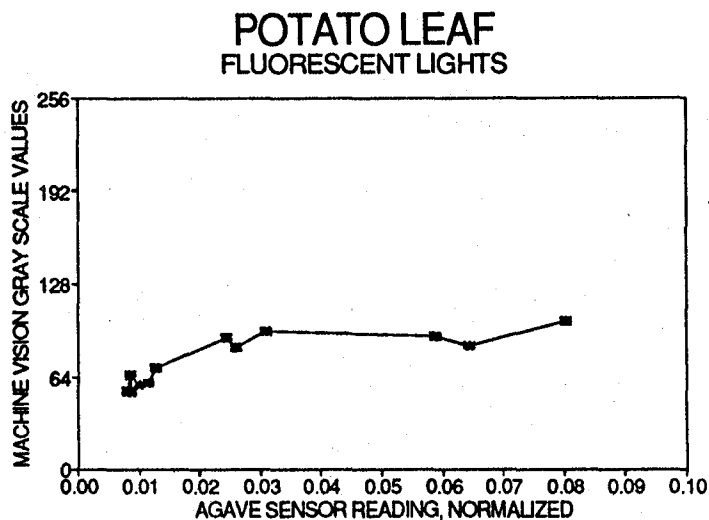


Figure 16. Machine Vision versus Multispectral Sensor Measurement of Norland Potato Leaf with Fluorescent Light.

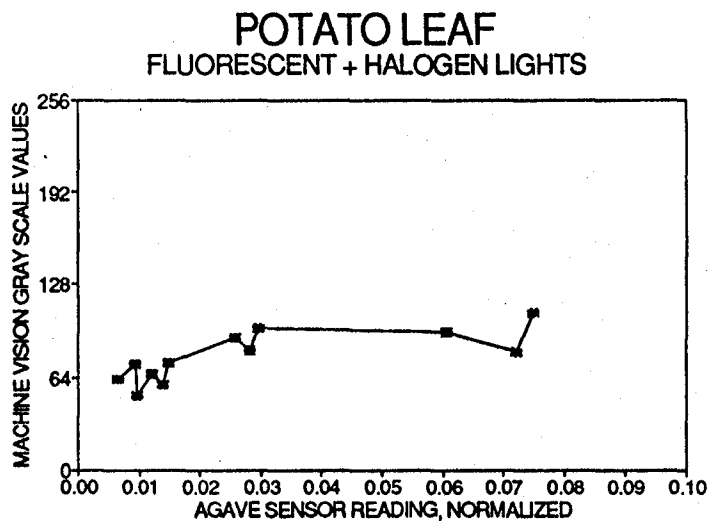


Figure 17. Machine Vision versus Multispectral Sensor Measurement of Norland Potato Leaf with Fluorescent and Halogen Lights.

CONCLUSIONS

The process of digitizing images with a Videopix card, then windowing and analyzing portions of the image using *sunvision* appears to satisfy the first objective. The C callable image processing library available with *sunvision* makes it attractive for use with CLIPS or other C-based expert system shell. Using narrow, band-pass optical filters proved successful for wavelengths less than 850 nanometers.

The machine vision gray scale values and the Agave multispectral sensor appear to correlate well for highly reflective surfaces, but not so well for lower reflectors, which include leaves. The differences in these sensors must be resolved before proceeding with the development of a machine vision sensor for monitoring the health and nutritional status of plants. Factors which may have contributed to differences included the lack of precise control over field of view and view angle for both sensors, and the fact that the multispectral sensor reading for each wavelength was computed for a band of approximately 50 nanometers either side of the central wavelength. The optical, bandpass filters used for the machine vision system have significant attenuation beyond 20 nanometers either side of the center wavelength. The difference caused by the angle of view can be seen in the potato leaves shown in Figure 2. This indicates that a laser or other structured light source will be required to determine the three-dimensional leaf surface, and thereby enable the sensor to be positioned normal to the surface. Further studies are necessary to quantify the differences due to view angle and to devise means of controlling view angle.

The results reported here were based on black and white images. There is considerable merit in exploring the use of the red, green, and blue planes of a color image. The videopix image digitizer, the Panasonic CCD camera, and *sunvision* software are capable of color image processing and further research with this system is urged.

REFERENCES

1. Al-Abbas, A. H., R. Barr, J. D. Hall, F. L. Crane, and M. F. Baumgardner. Spectra of Normal and Nutrient-Deficient Maize Leaves. Agronomy Journal. Vol. 66. Jan-Feb pp 16-20.
2. Ruiz, Margarita and Pictiaw Chen. Use of the First Derivative of Spectral Reflectance to Detect Mold on Tomatoes. Transactions of the ASAE. 1982. Vol 25 No 3 pp 759-762.
3. Stutte, G. W., R. Bors, and C. A. Stutte. Quantification of Nutrient Stress from Video Images. Horticultural Science. 1989. Vol 24. p. 75.
4. Miles, Gaines E. Plant Features Measurements for Robotics. NASA/ASEE Summer Faculty Fellowship Program. Kennedy Space Center Florida. 1989. 22p.
5. Latin, R. X., G. E. Miles, J. C. Rettinger, and J. R. Mitchell. An Expert System for Diagnosing Muskmelon Disorders. Plant Disease. 1990. Vol 74. No 1. pp 83-87.